

*Citation for published version:*

Brady, A, Faraway, J & Prosdocimi, I 2018, 'Attribution of large-scale drivers of peak river flows in Ireland', Paper presented at International Workshop on Statistical Modelling 2018, Bristol, UK United Kingdom, 15/07/18 - 20/07/18 pp. 54-58.

*Publication date:*  
2018

*Document Version*  
Peer reviewed version

[Link to publication](#)

**University of Bath**

## **Alternative formats**

If you require this document in an alternative format, please contact:  
[openaccess@bath.ac.uk](mailto:openaccess@bath.ac.uk)

### **General rights**

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

### **Take down policy**

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

# Attribution of large-scale drivers of peak river flows in Ireland

Aoibheann Brady<sup>1</sup>, Julian Faraway<sup>1</sup>, Ilaria Prosdocimi<sup>1</sup>

<sup>1</sup> University of Bath, United Kingdom

E-mail for correspondence: [a.brad@bath.ac.uk](mailto:a.brad@bath.ac.uk)

**Abstract:** Several large flooding events in recent years have led to increased concerns that climate change may be affecting the risk of flooding. At-site tests assessing whether change can be detected in observed data are not very powerful and cannot fully differentiate between possible confounders. It is also difficult to detect fully climate-driven trends, and separate these from other anthropogenic impacts such as urbanisation. We propose a change in focus from detection only towards both detecting and attributing trends in peak river flows to large-scale climate drivers such as the North Atlantic Oscillation index. We focus on a set of near-natural “benchmark” catchments in Ireland in order to detect those non-human driven trends. In order to enhance our ability to detect a signal, we model all stations together in a Bayesian framework which is implemented through Stan.

**Keywords:** Bayesian hierarchical models; Detection & attribution; Flood risk.

## 1 Problem

Ireland has been hit by a number of severe floods in recent years, leading to concerns of an increased frequency and severity of floods. Climate change projections allude to increases in extreme precipitation (Bates (2009)), with the belief that this may contribute to an increase in peak river flows. These possible changes in flood risk are derived from climate change projections, however at-site tests using the (relatively short) observed river flow data records do not display compelling evidence of increasing trends. Such tests are not very powerful in a statistical sense. Current flood risk estimation approaches largely assume stationarity of the river flow process, which in practice means assuming the probability of an extreme event is constant. This approach can fail to accurately estimate the frequency of extreme flooding events, which can be extremely costly to the government and the

---

This paper was published as a part of the proceedings of the 33rd International Workshop on Statistical Modelling (IWSM), University of Bristol, UK, 16-20 July 2018. The copyright remains with the author(s). Permission to reproduce or extract any parts of this abstract should be requested from the author(s).

public alike. Consistently underestimating any trends in peak river flows may mean that flood infrastructures are unfit for purpose for future extreme events. Another issue is the focus on the detection of time trends, rather than attributing any such trends to a variable of interest. It is also often challenging to separate out anthropogenic changes from natural climate variability, making it difficult to accurately attribute any such trends.

We propose a new method for investigating potential drivers of peak river flows in Ireland, taking into account each of these issues. We focus on a combined approach of the detection and attribution of trends. We investigate the effect of large-scale climate indices such as the North Atlantic Oscillation and East Atlantic index on peak river flows in Ireland. We model all stations together within a Bayesian multilevel framework, both to improve the power of such models and to make use of the natural hierarchical structure of spatial data. Many of the river gauging stations are geographically or hydrologically close to each other, and we might expect trends of these nearby stations to be similar. Including all stations in a model together with a spatial random effect to account for correlation between sites may help us to obtain evidence of any trends in river flows that would have been too weak to detect otherwise. Finally, we focus on a set of near-natural “benchmark” catchments in order to detect those trends driven by natural climate variability.

## 2 Data

We focus on annual maximum river flow data from both the Republic of Ireland and Northern Ireland across a series of reference benchmark catchments introduced by Murphy et al. (2013) and Harrigan et al. (2017). These reference catchments have long records of good hydrometric quality, are relatively near-natural and representative of the land’s hydrology. They were chosen to overcome the difficulty in accurately attributing climate-driven trends, which may be due to human impact and changes in hydrometric performance in gauging stations over time.

The annual maximum series for benchmark catchments for Northern Ireland was obtained from the UK National River Flow Archive, while data for the Republic of Ireland was obtained through the Office of Public Works hydrometric database. The merged data set contains the largest observed instantaneous peak flows at each station in each water year (which run from October to September), measured in  $\text{m}^3/\text{s}$ . In total, there are 1,660 observations from 35 gauging stations, ranging from 1950-2015.

We focus on the combined approach of the detection and attribution of trends, by investigating the relationship between peak river flows and large-scale climate indices such as the North Atlantic Oscillation (NAO) or the East Atlantic (EA) Index. These indices are impacted by climate change in a more direct manner than precipitation, so they are proxies for climate

which is changing (but are also quite variable to begin with). Both the NAO and EA are models of natural climate variability, which impact the weather and climate of the Atlantic and Europe. Monthly data for both of these indices was obtained from the National Oceanic and Atmospheric Administration website.

### 3 Methods

We utilise the fact that nearby stations can be expected to be impacted in a similar way by external variables. The model is written as the combination of some overall trend, a random effect to account for measurement correlation at each station, and a random effect which has some spatial structure. For station  $i$  at time  $t$ , we have:

$$\log(\text{Flow})_{it} = \alpha + \mathbf{X}_t\boldsymbol{\beta} + r_i + s_i + \epsilon_{it}, \quad (1)$$

where  $X$  is the matrix of explanatory variables we are investigating,  $\epsilon_i \sim N(0, \sigma_i^2)$  is the measurement error,  $r_i$  is a random effect to allow for variation between stations and  $s_i$  is a spatial random effect ( $s \sim \text{MVN}(0, \Sigma)$ ) to allow for correlation between nearby stations. We utilise an exponential correlation structure, where distance is based on the Euclidean distance between sites  $i$  and  $l$ , which we model through a Gaussian process (GP) given by

$$K(x|\eta, \rho)_{il} = \eta^2 \exp\left(\frac{-d_{il}}{\rho}\right).$$

The hyper-parameter  $\rho$  describes the characteristic length-scale over which sites  $i$  and  $l$  influence each other, while  $\eta$  is the marginal standard deviation controlling the magnitude of the function's range. Following the recommendations of Gelman et al. (2017), we use weakly informative priors for these parameters. These models are implemented through Stan.

### 4 Results & Analysis

We investigate models relating the log of the annual maximum flows to time, NAO, EA and combinations of these in a preliminary analysis. Figure 1 suggests that both EA and time are associated with the log of the peak flows, but not NAO. However, when NAO is modelled alone (not shown here), there appears to be a clear association with peak flows. This suggests that there may be some time-varying confounding which we need to account for when attributing the effect of climate indices on peak flows. Mapping the spatial random effect  $v_i$  in Figure 2 shows that there appears to be some spatial clustering of trends, particularly in the south east. This will be explored in a future analysis.

#### 4 Attribution of large-scale drivers of peak river flows in Ireland

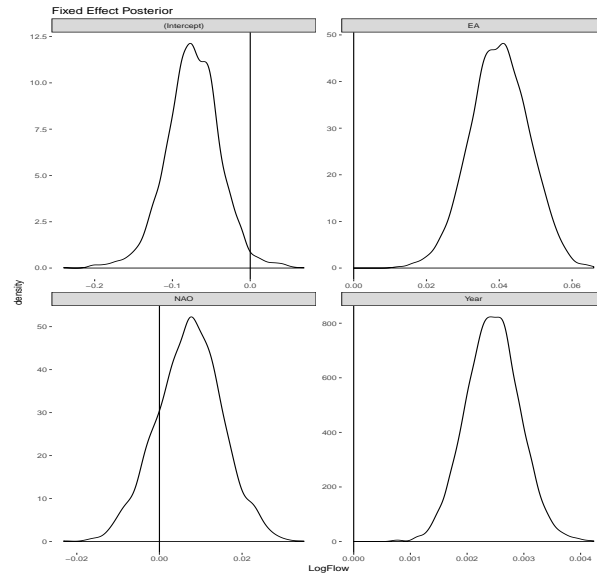


FIGURE 1. Fixed effect posterior distributions

Spatial random effect

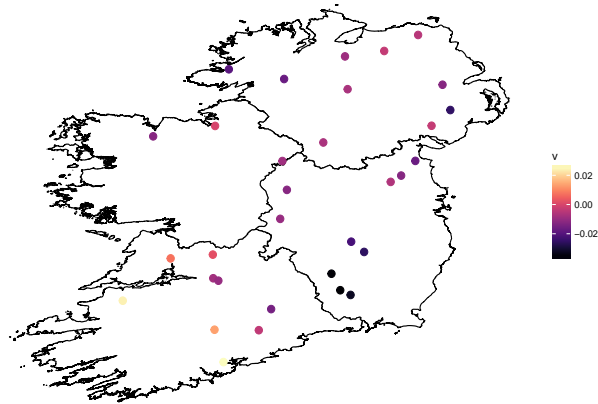


FIGURE 2. The spatial correlation structure

This preliminary analysis suggests that peak river flows in Ireland are associated with both time and climate indices. However, it is likely that both

the EA and NAO are confounded with time, which must be accounted for in future approaches. In addition, a causal framework must be explored in order to accurately attribute the impact of these climate indices on peak river flows in Ireland.

## References

- Bates, B. (2009). Climate Change and Water: IPCC technical paper VI *World Health Organization*.
- Harrigan, S. and Hannaford, J. and Muchan, K. and Marsh, T. (2017). Designation and trend analysis of the updated UK Benchmark Network of river flow stations: The UKBN2 dataset. *Hydrology Research*, **49**(1).
- Murphy, C. and Harrigan, S. and Hall, J. and Wilby, R. L. (2013). HydroDetect : The Identification and Assessment of Climate Change Indicators for an Irish Reference Network of River Flow Stations. Climate Change Research Programme (CCRP) 2007-2013 Report Series No. 27. *Technical Report. Environmental Protection Agency, Co. Wexford*.
- Gelman, A. and Simpson, D. and Betancourt, M. (2017). The prior can generally only be understood in the context of the likelihood. *Entropy*, **19**(10).